NOAA FISHERIES

Fisheries Ecology Division

3.3 Towards model-free ecosystem management:

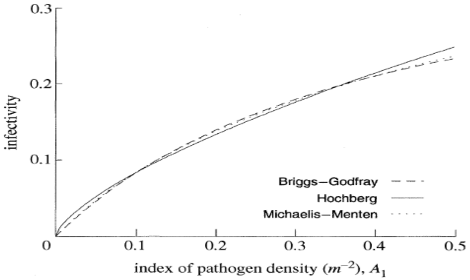
Nonlinear time series analysis for EBFM and testing with mesocosm experiments.

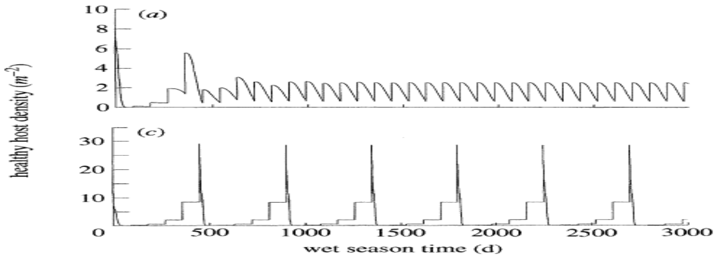
Stephan B. Munch

Motivation: Structural uncertainty

- Species interactions are difficult to quantify and highly context specific
- Ecosystem models can be extremely sensitive to model structure

$$\frac{dH}{dt} = -f(A_1)H,$$
$$\frac{dA_1}{dt} = c(A_0 - A_1),$$
$$\frac{dA_0}{dt} = c(f(A_1(t-\tau))H(t-\tau) - A_0).$$

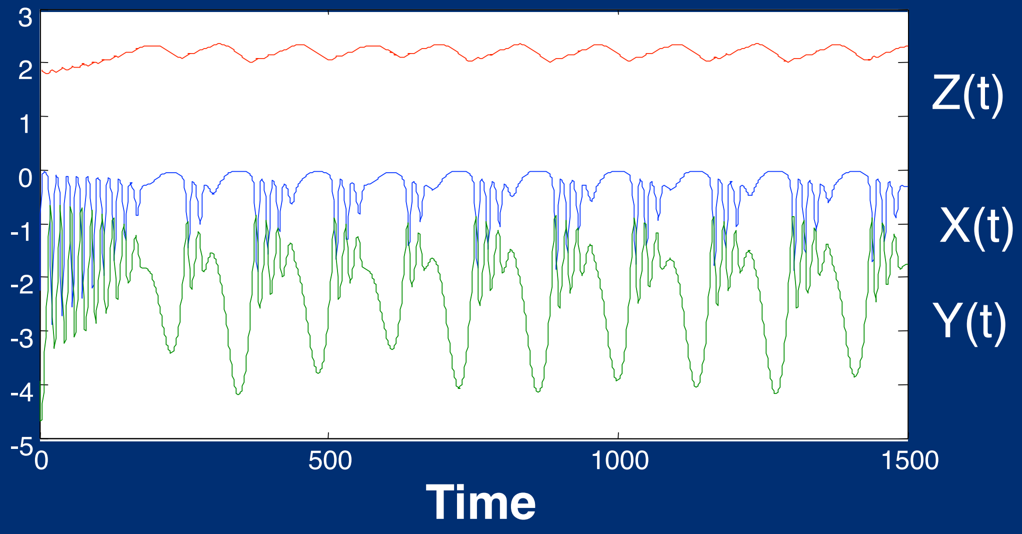


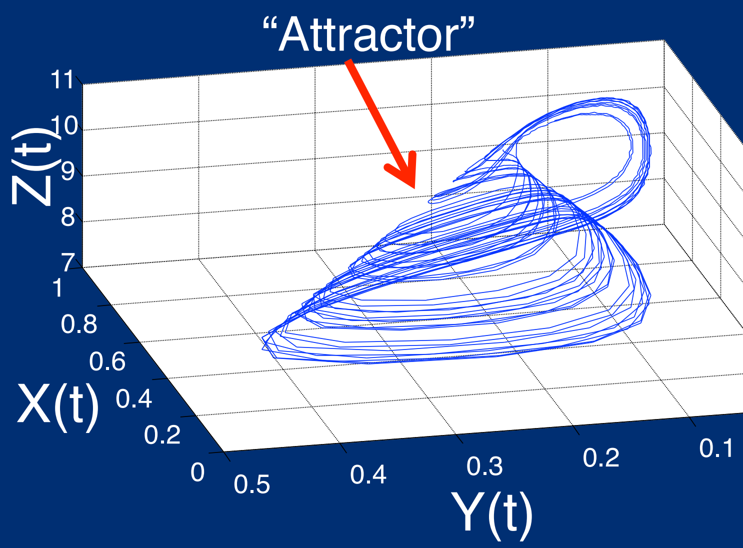


Is there some way to avoid these problems?

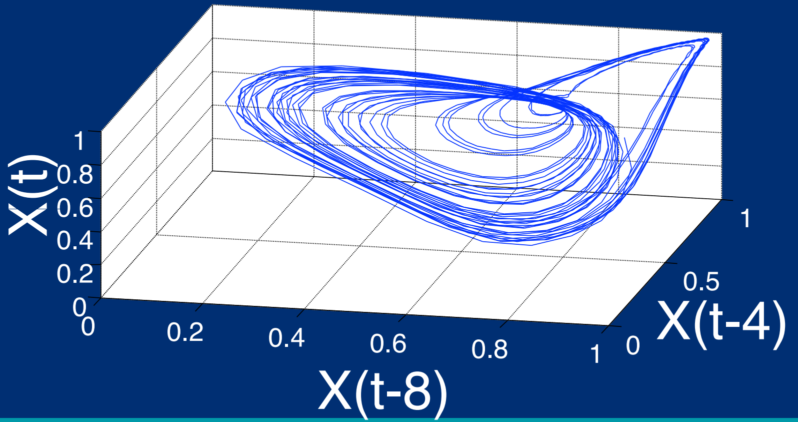
Time-delay embedding

Some 3-species system

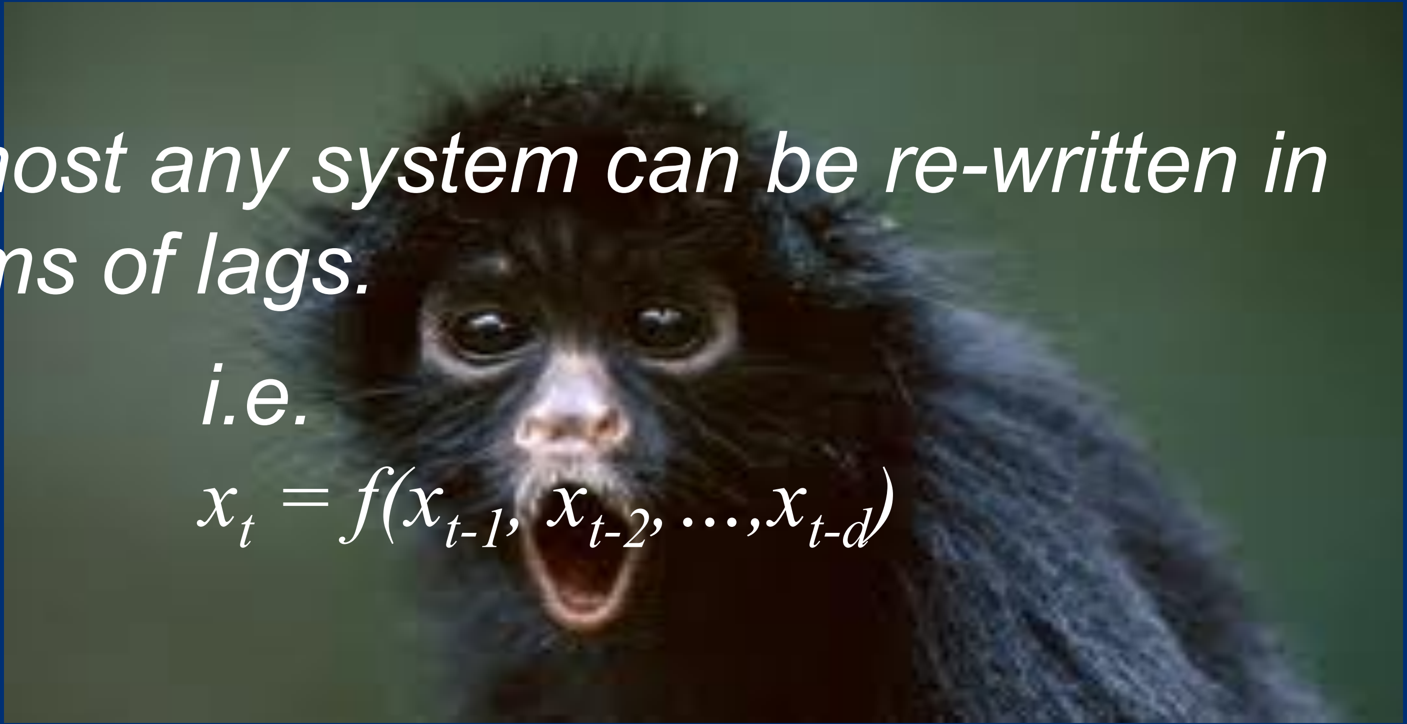




Time-delay embedding



Takens' Delay Embedding Theorem



Almost any system can be re-written in terms of lags.

i.e.

$$x_t = f(x_{t-1}, x_{t-2}, \ldots, x_{t-d})$$

Can use more than one time series if you have it

Methods to date

- Forecasting in many disciplines
- Identify dynamic coupling from time series
- Quantify context-dependent interactions
- Always better at forecasting than using the wrong parametric model, sometimes better than fitting the right one!
- Correct for model mis-specification

Detecting Causality in Complex Ecosystems

George Sugihara,[1*] Robert May,[2] Hao Ye,[1] Chih-hao Hsieh,[3] Ethan Deyle,[1] Michael Fogarty,[4] Stephan Munch[5]

Tracking and forecasting ecosystem interactions in real time

Ethan R. Deyle[1], Robert M. May[2], Stephan B. Munch[3] and George Sugihara[1]

Model-free forecasting outperforms the correct mechanistic model for simulated and experimental data

Charles T. Perretti[a,1], Stephan B. Munch[b], and George Sugihara[a]

Reply to Hartig and Dormann: The true model myth

Charles T. Perretti[a,1], Stephan B. Munch[b], and George Sugihara[a]

A Bayesian approach to identifying and compensating for model misspecification in population models

James T. Thorson,[1,4] Kotaro Ono,[2] and Stephan B. Munch[3]

Nonparametric forecasting outperforms parametric methods for a simulated multispecies system

Charles T. Perretti,[1,3] George Sugihara,[1] and Stephan B. Munch[2]

Current developments

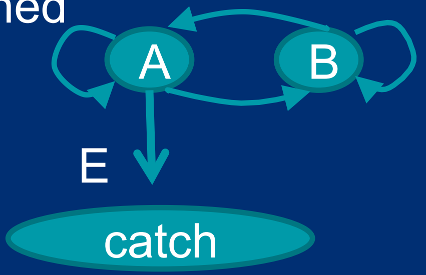
- Hierarchical modeling of short time series
- Methods for non-stationary systems
- Developing leading indicators of regime shifts
  - for general bifurcations and unstable systems
- Harvest policy from forecasts
- Test in laboratory mesocosms

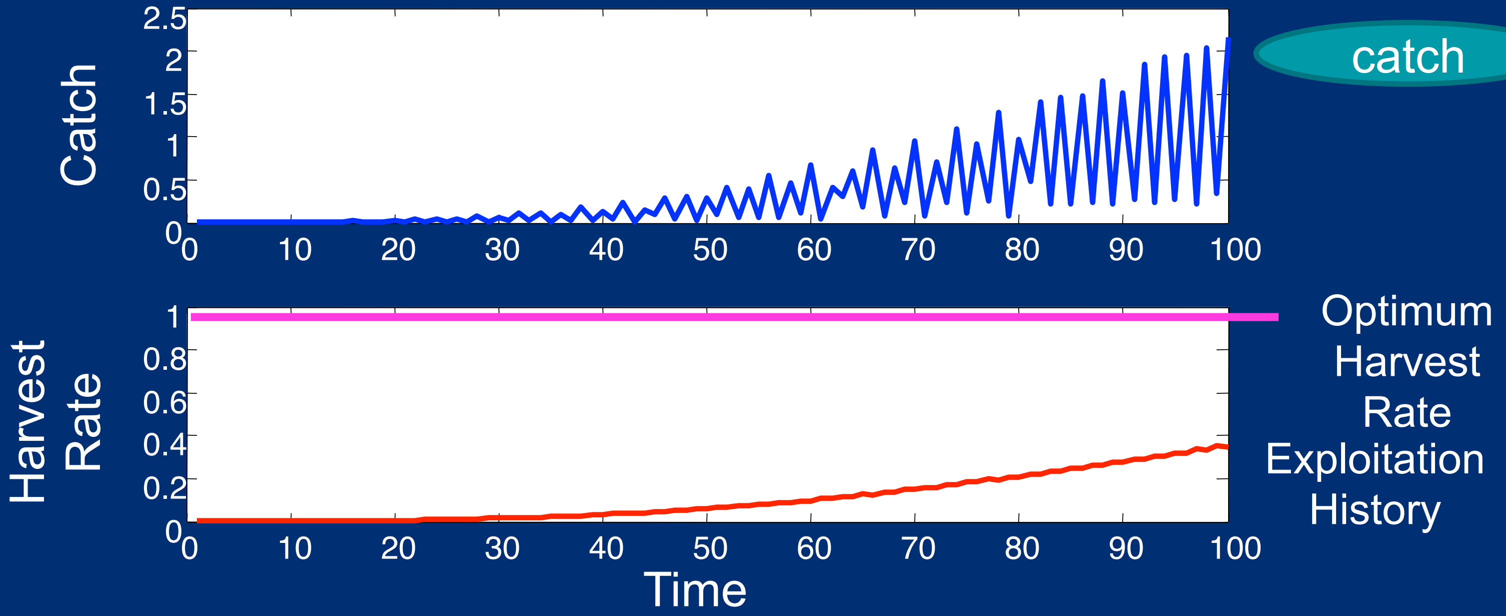
Avoiding tipping points in fisheries management through Gaussian process dynamic programming

Carl Boettiger[1], Marc Mangel[1] and Stephan Munch[2]

Simulations

Two classes (species, locations, etc)
One fished





Management from forecasts: Empirical dynamic programming

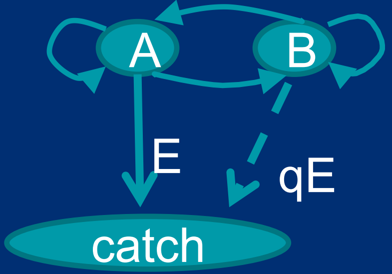
1. Forecast population size in terms of previous size and catch (yield)

$$x_t = f(\underbrace{x_{t-1},\ldots,x_{t-d}}_{\text{population size}},\underbrace{y_t,\ldots,y_{t-d}}_{\text{catch}}) + \varepsilon_t$$

2. Find harvest policy that maximizes long-run discounted average reward using stochastic dynamic programming

$$V(\vec{x}_t,\vec{y}_t) = \max_{y_t} \mathrm{E}\left\{R(\vec{x}_t,\vec{y}_t) + \gamma V(\vec{x}_{t+1},\vec{y}_{t+1}) \mid \vec{x}_t,\vec{y}_t\right\}$$

3. Compare long-run yield to single-species policy and optimal policy for 5 different 2d scenarios



Yield ratio:

100 years total yield: EDP policy

(from training data)

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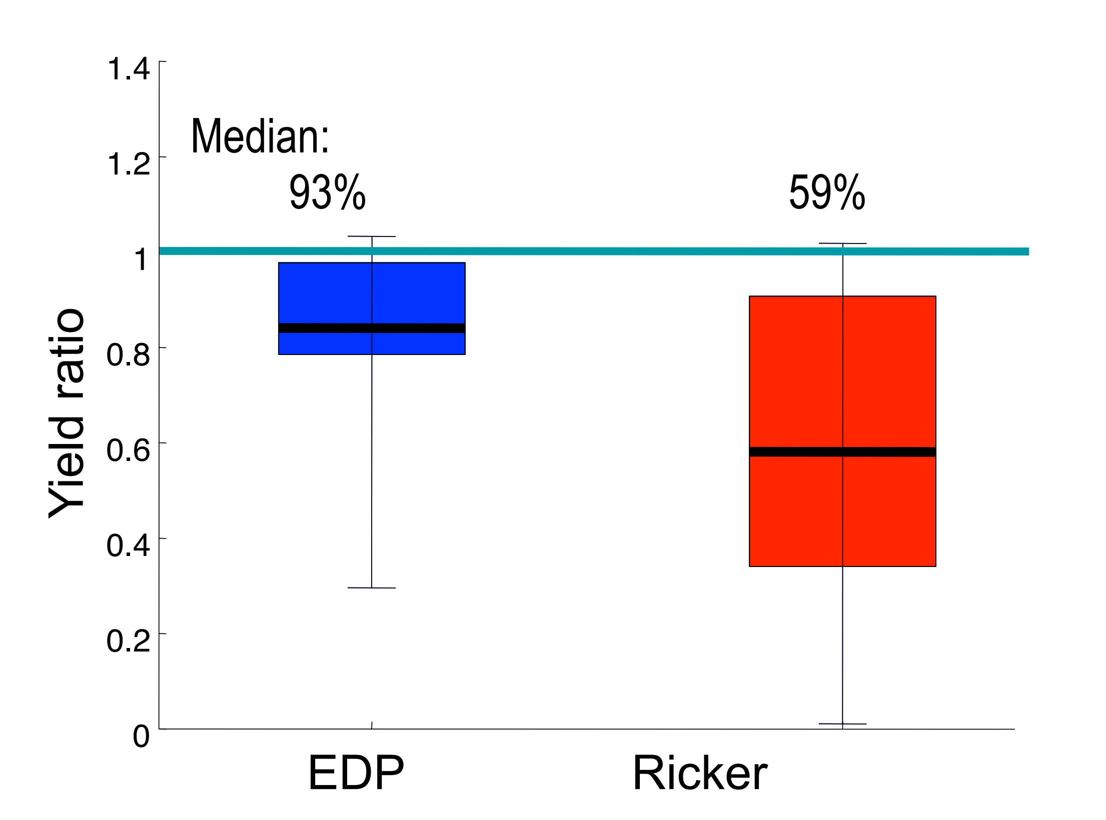
100 year total yield: Optimal policy

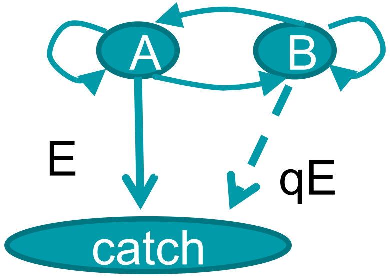
(from 'true' model)

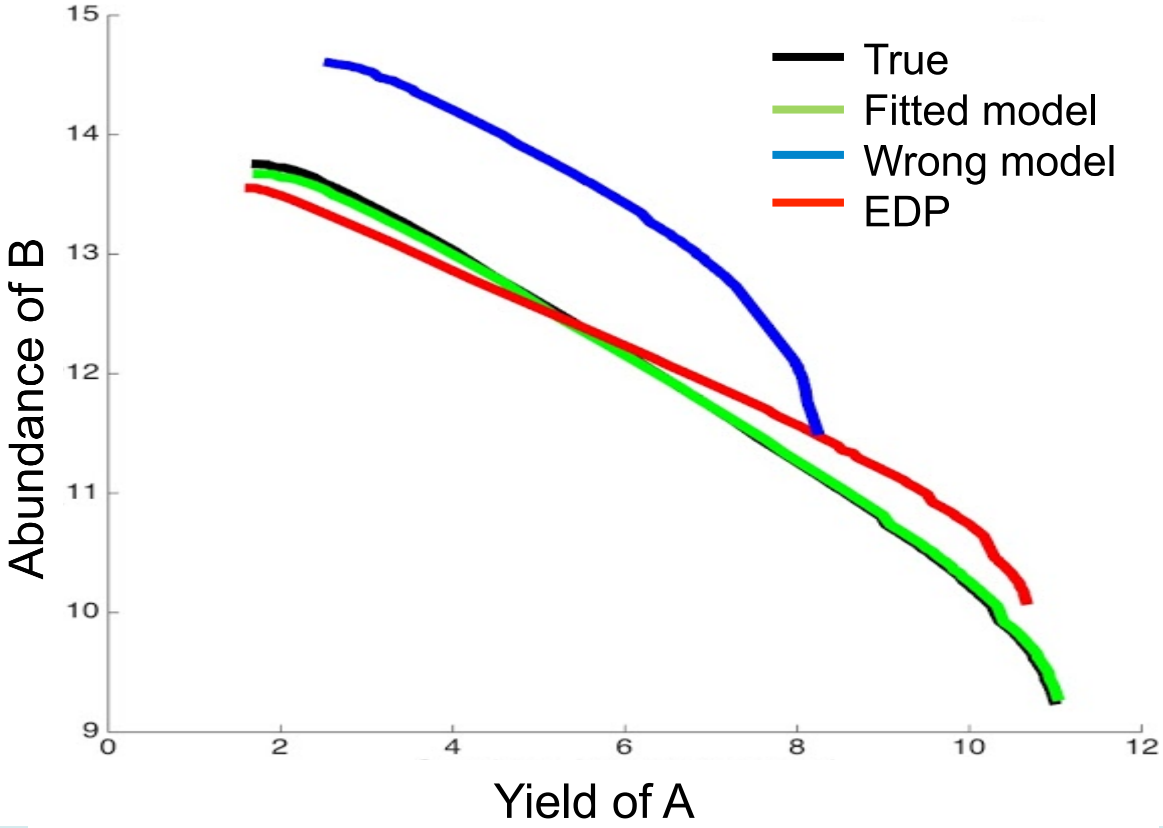
Overall performance (in 32,400 simulations)



Multi-objective programming: Pareto front

Trade-off between exploitation of A and conservation of B





Mesocosm Experiments

Five gallon mesocosms
Constant or variable temperature
Seeded with:

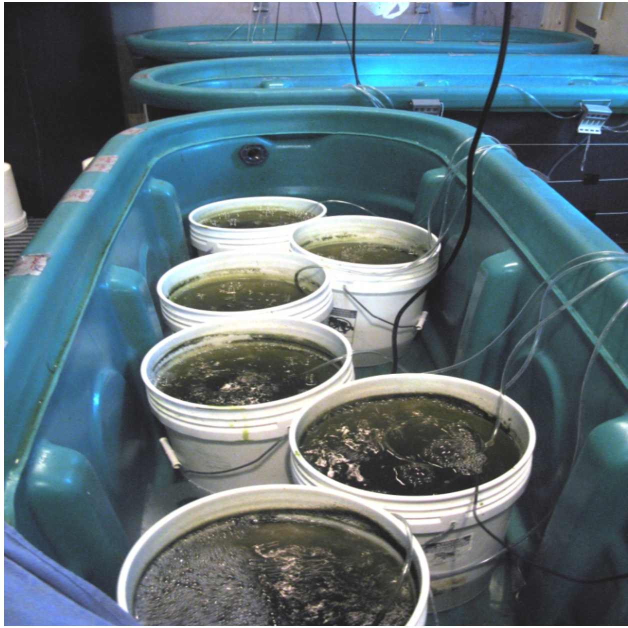
Rotifers (*Brachionus plicatilis*)
- mature in 2-3 days, live 10-30 days

Artemia (*Artemia salina*)
- 15 life stages, mature in 2-6 weeks, live 2-6 months

Open to invasion:

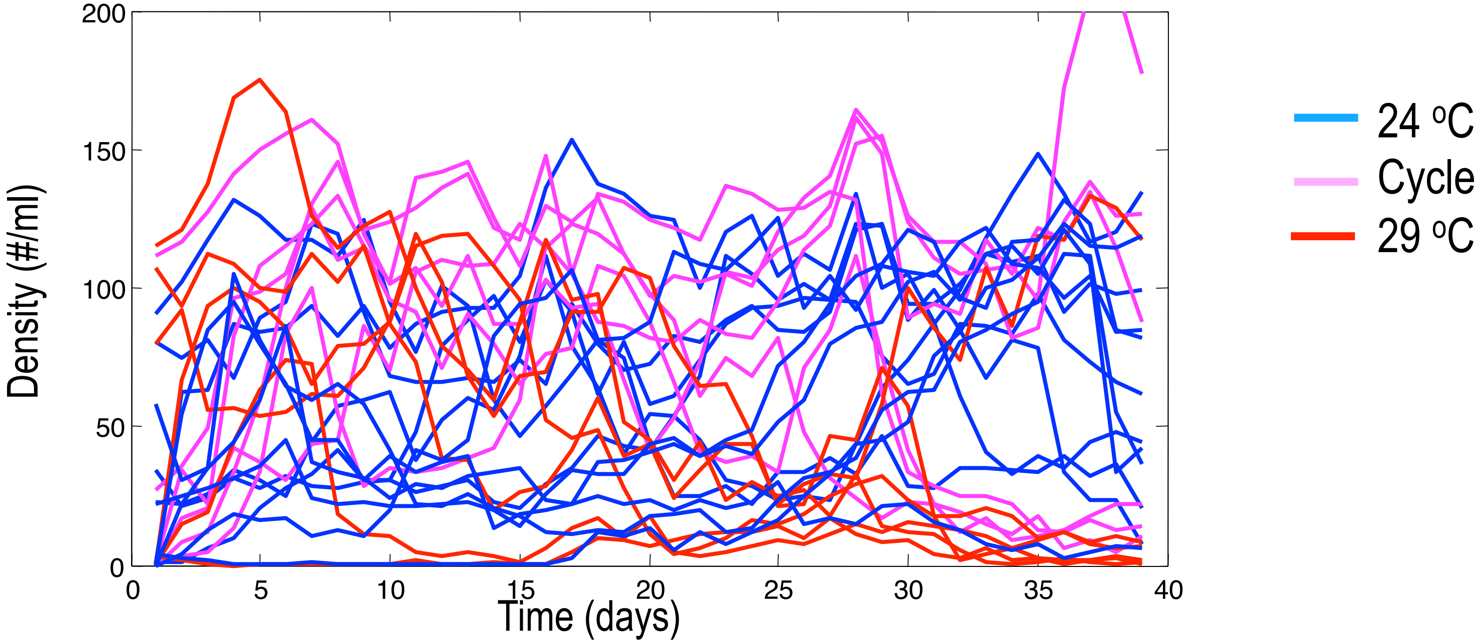
by ciliates, nematodes, other rotifers, bacteria

Three management regimes-
Single-species model, EDP, and unmanaged controls

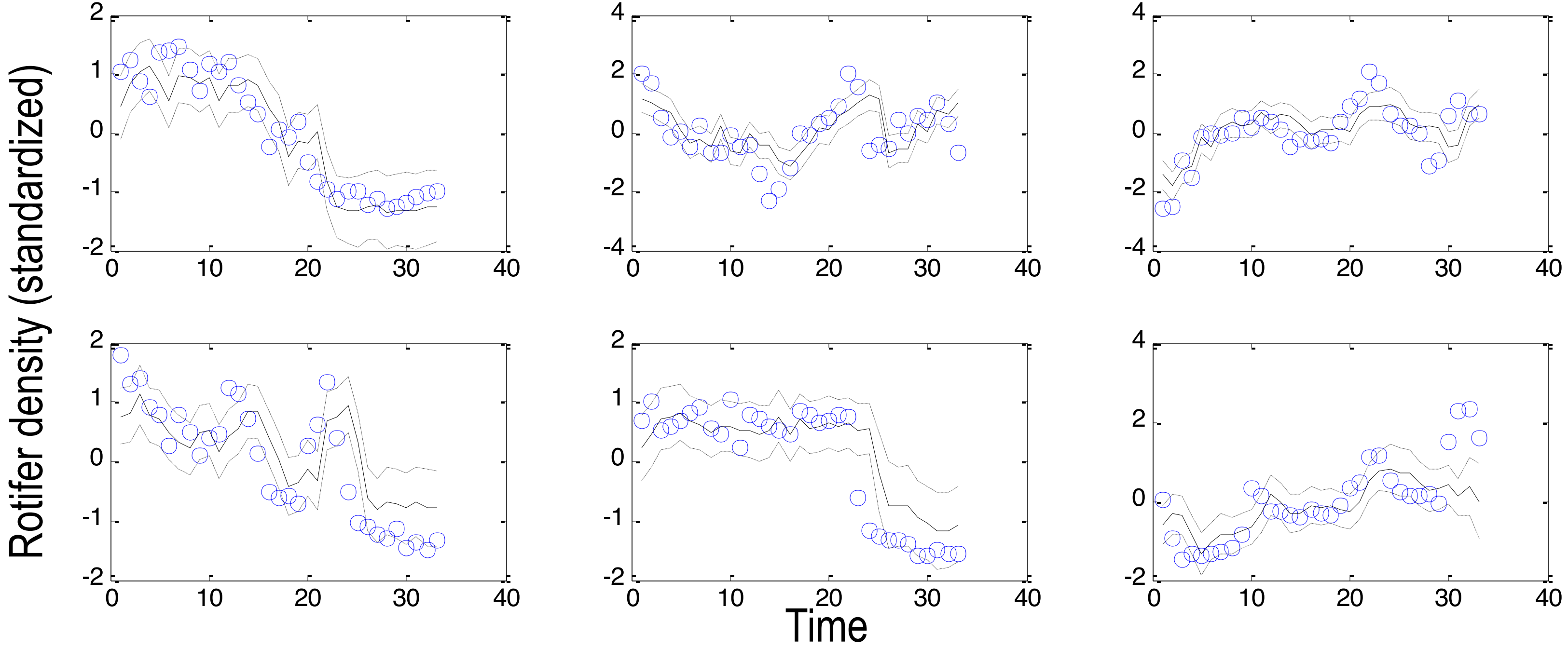


Rotifer-Artemia
'Ecosystem'
management

Mesocosm time series



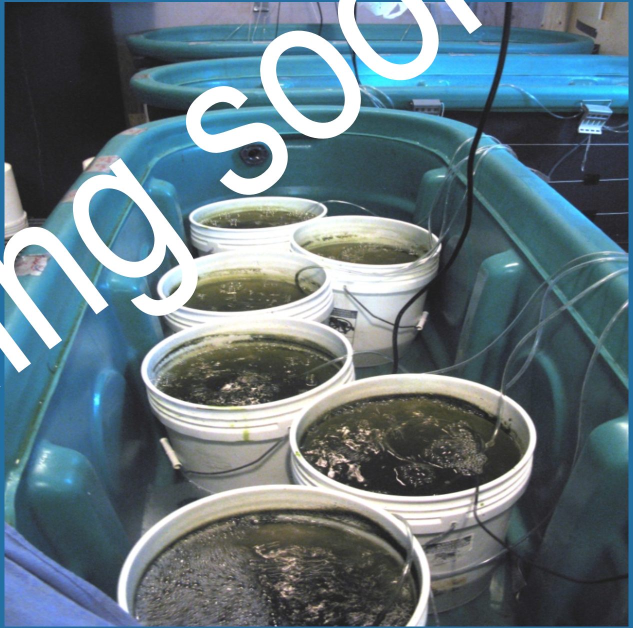
Two-day forecasts



Time series for cyclic temp treatment: E=3, Lag = 2

Rotifer and Artemia management

Coming soon!



Strengths

Approach is generic – should work whenever data are sufficient

Always better than the wrong parametric model

Challenges

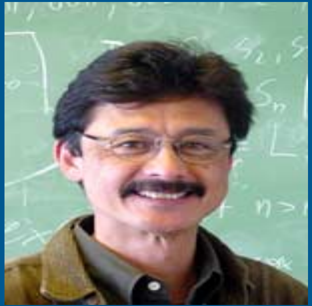
Scaling up to many species, space

Future Directions

Integrate prior information

Convince someone to try this in the field

Collaborators


George Sugihara


Carl Boettiger


Valerie Poynor

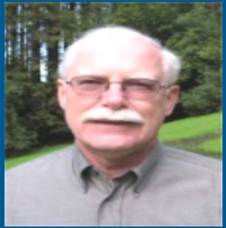

Jo Anne Siskidis


Jim Thorson

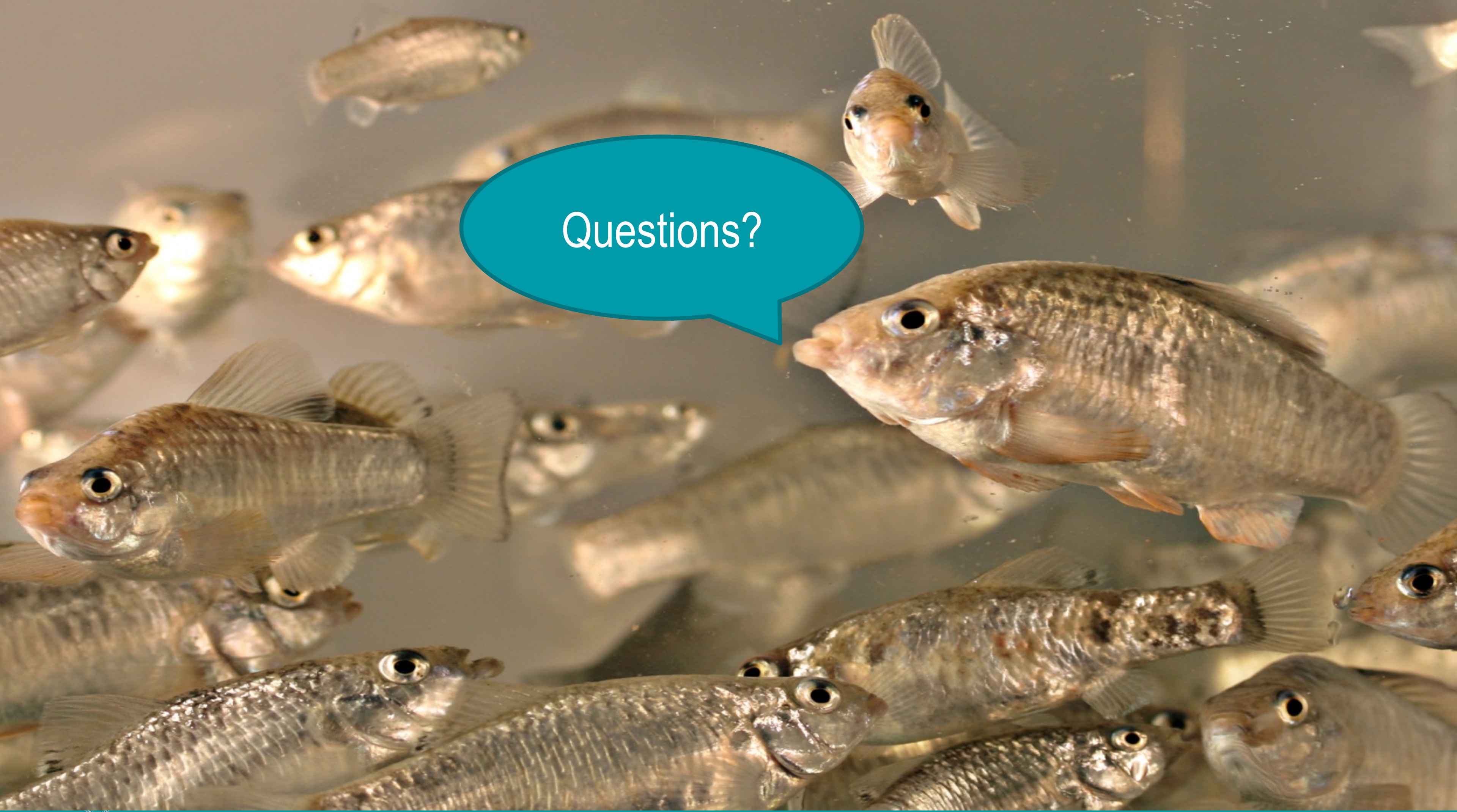

Charles Perretti


Ethan Deyle


Juan Lopez Arriaza

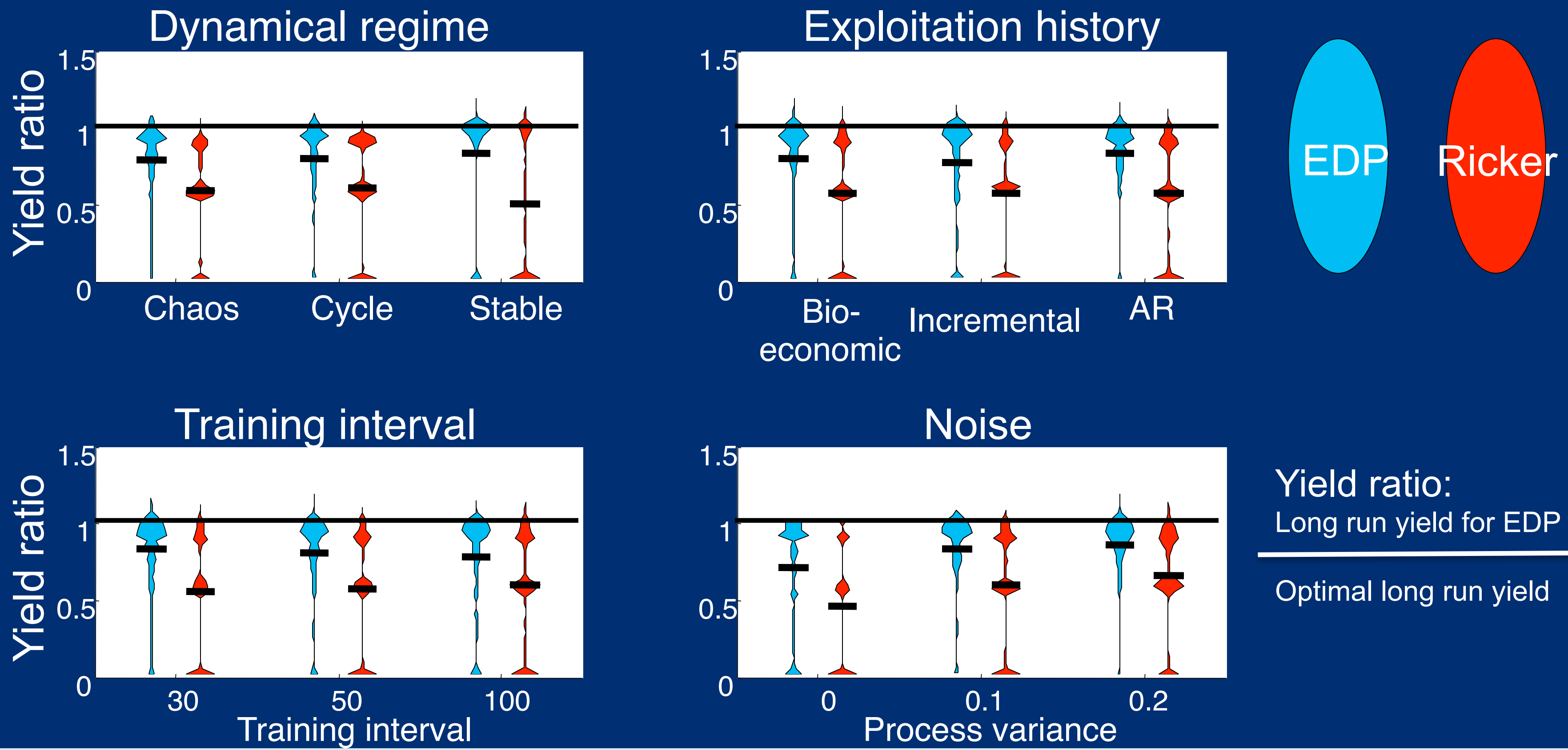

Alec MacCall


Marc Mangel


Questions?

Slides for anticipated questions below

EDP produces near-optimal yield



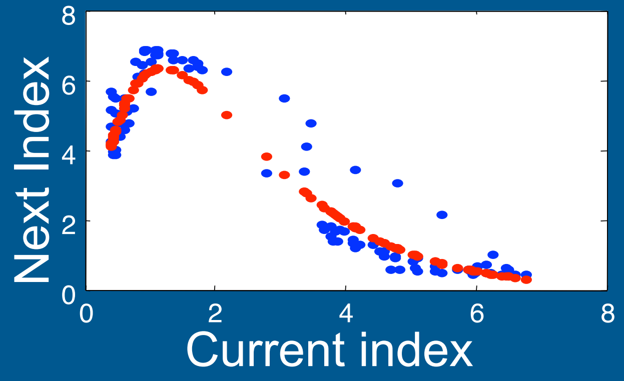
Yield ratio:

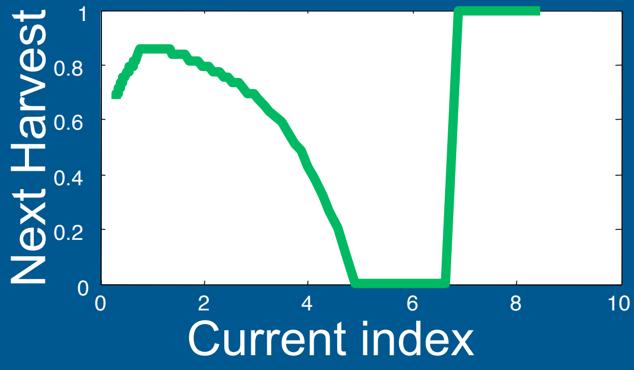
$$\frac{\text{Long run yield for EDP}}{\text{Optimal long run yield}}$$

Fit to data & Forecast

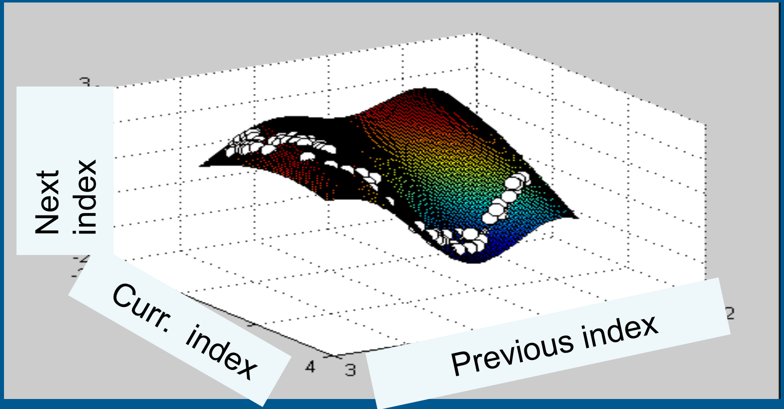
Policy

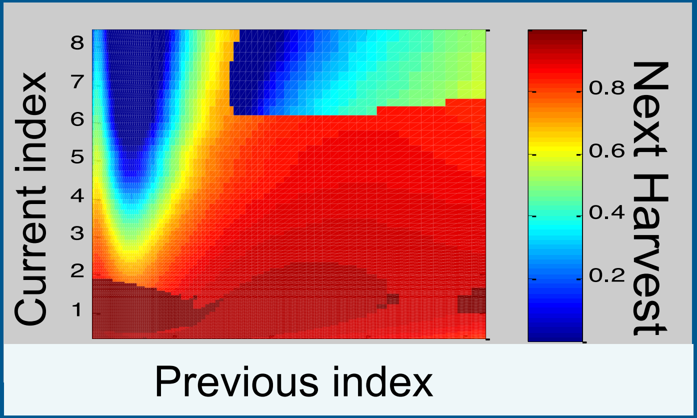
Ricker

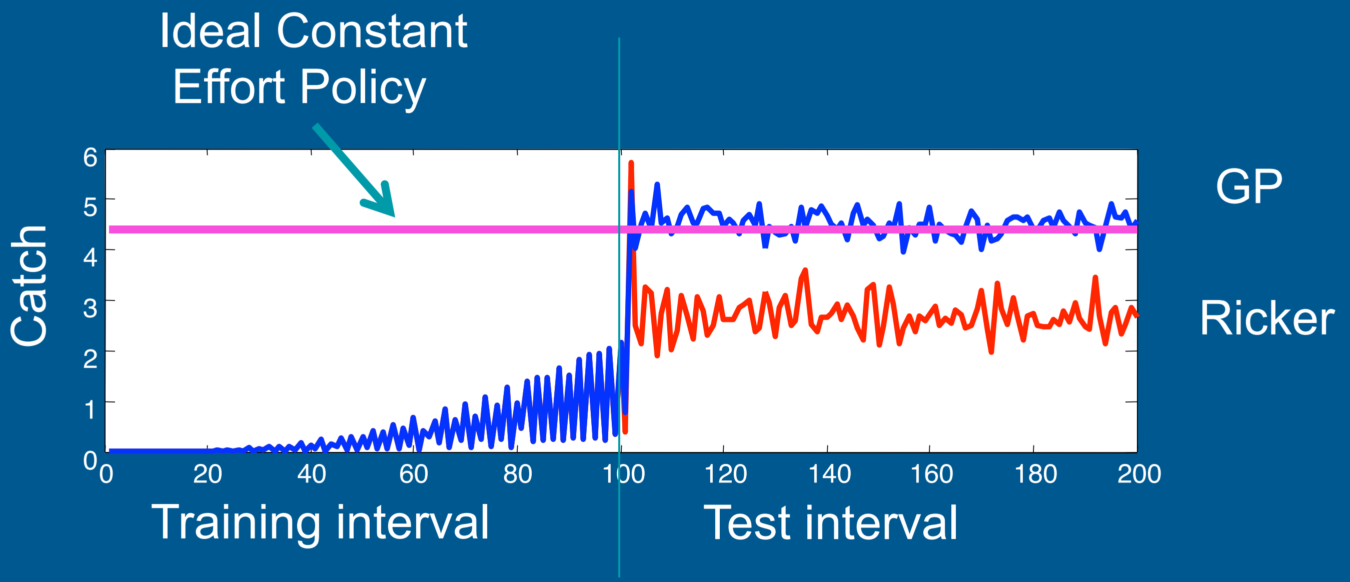




GP







Two standards:

1. Constant harvest policy based on perfect information
   Unrealistic ideal
2. Policy based on Ricker model fit to same time series
   Close to what is done in 'data-limited' fisheries

Avoiding collapse

"Ricker" (Model with *no tipping point*)

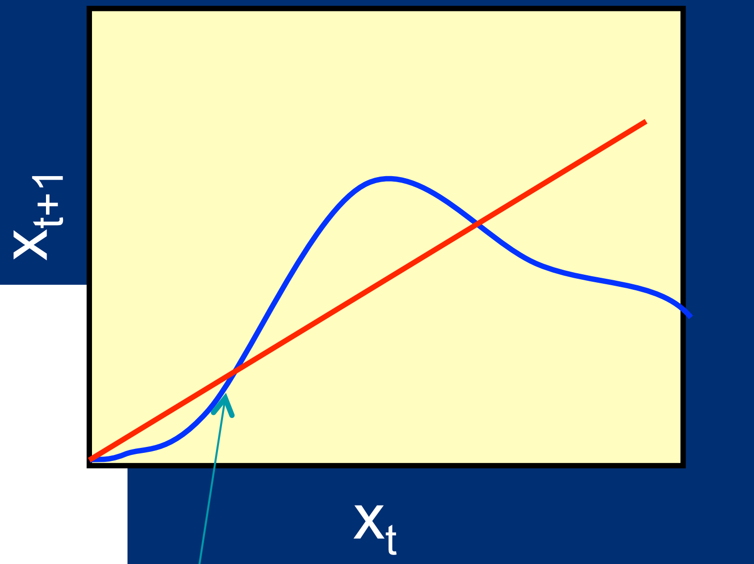
$$X_{t+1} = S_t e^{r_0(1-S_t/K)}$$

"Myers" (First *tipping point* model)

$$X_{t+1} = \frac{aS_t^{\alpha}}{1 + S_t^{\alpha}/b}$$

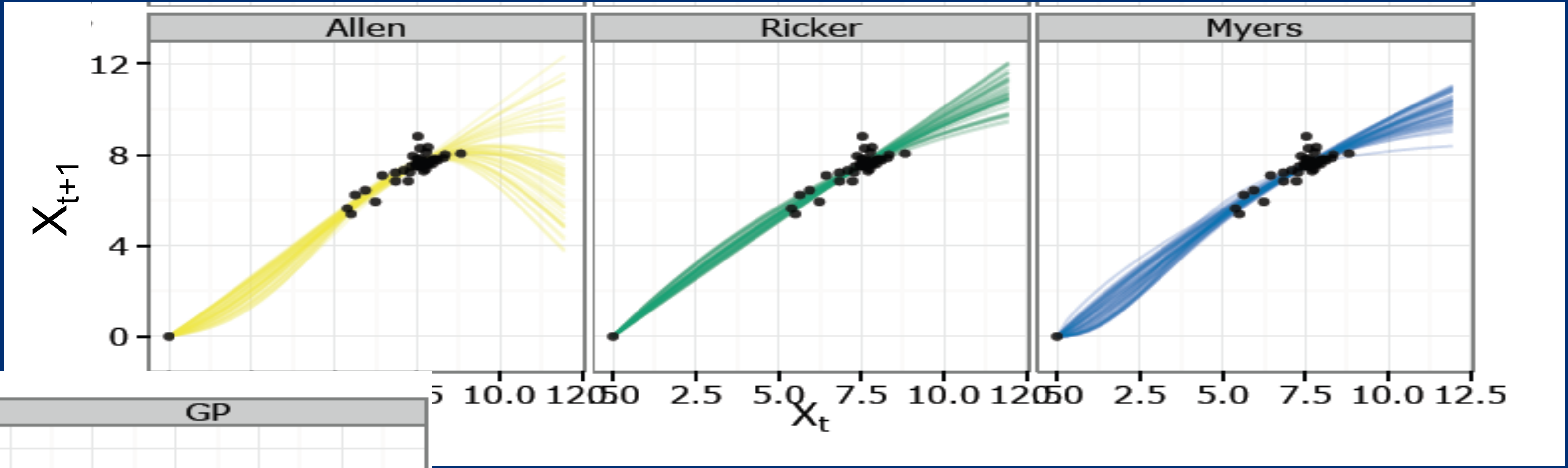
"Allen" (Second *tipping point* model)

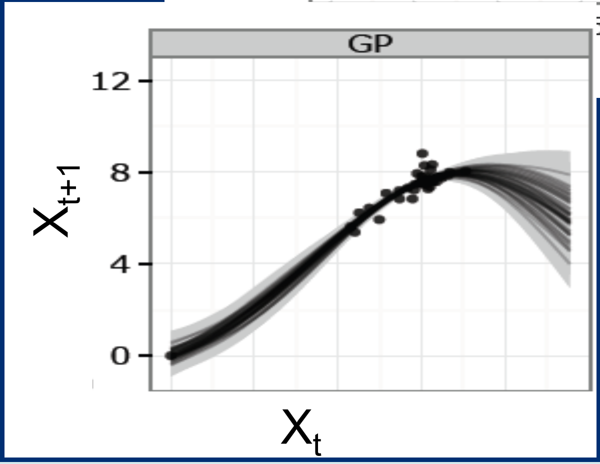
$$X_{t+1} = S_t e^{r\left(1-\frac{S_t}{K}\right)(S_t-C)}$$



Simulation model has 'tipping point'

Model selection favors simpler model

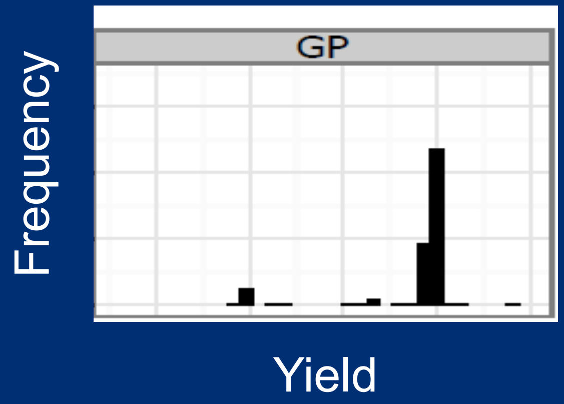




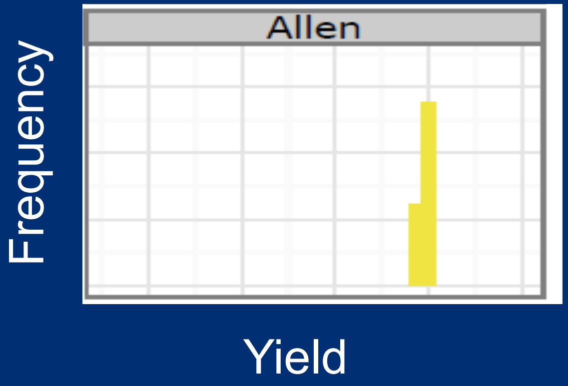
	Ricker	Myers	Allen
DIC	**49.45**	50.61	50.14
AIC	**-30.07**	-27.19	-24.60
BIC	**-25.00**	-20.44	-17.85

Policy evaluation

-Dynamic programming to derive policy
-Determine 50 year average yield
-100 simulations



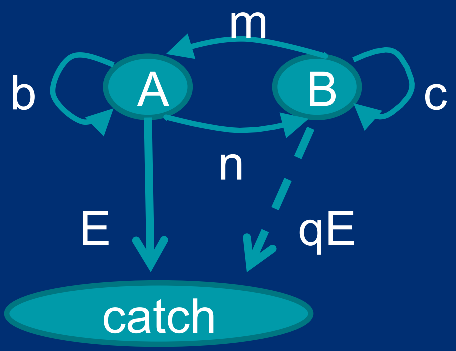
Fitted ‘true’ model



Policy based on ‘best’ model drives population extinct!

What happens if we also harvest fish from the other location (or the other species) ?

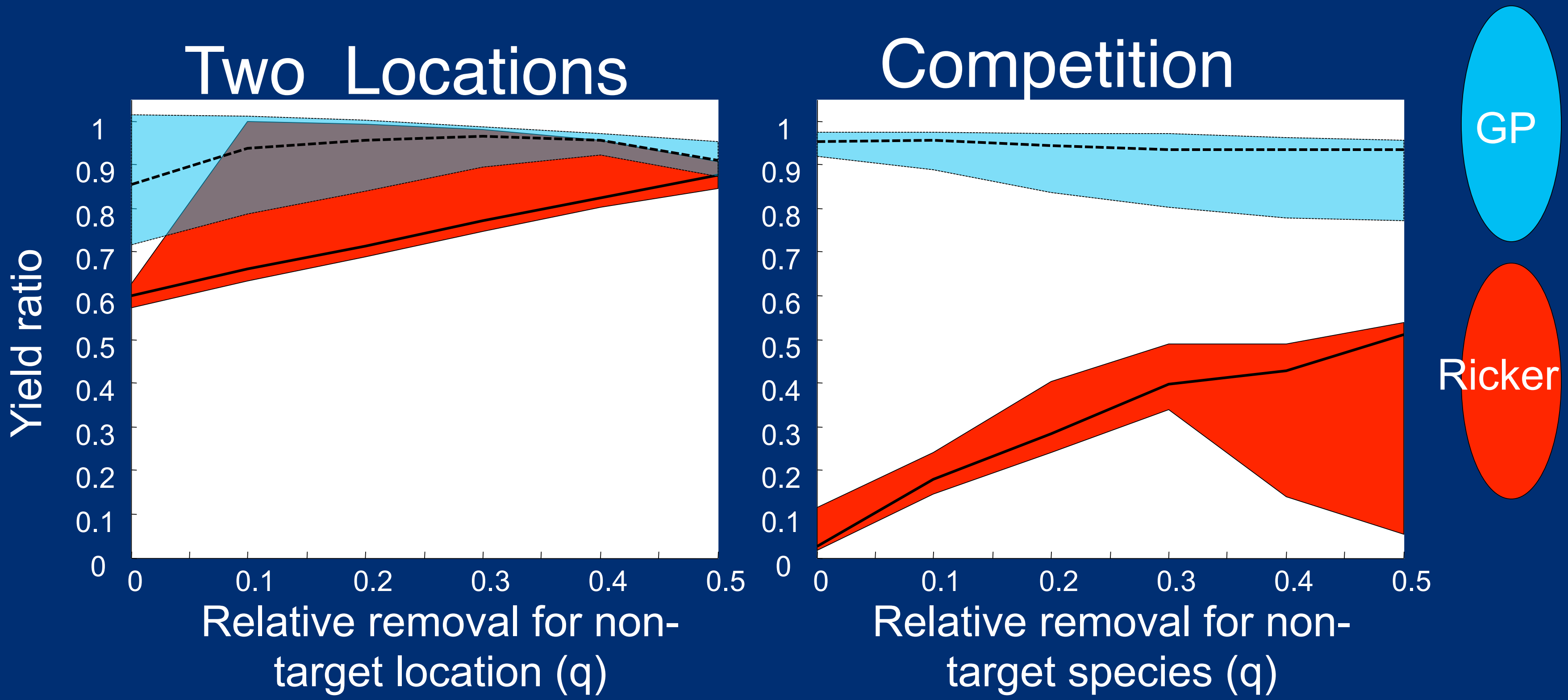
Imperfect ‘selectivity’



q<1

Everything else stays same-

still only know total catch and nominal effort



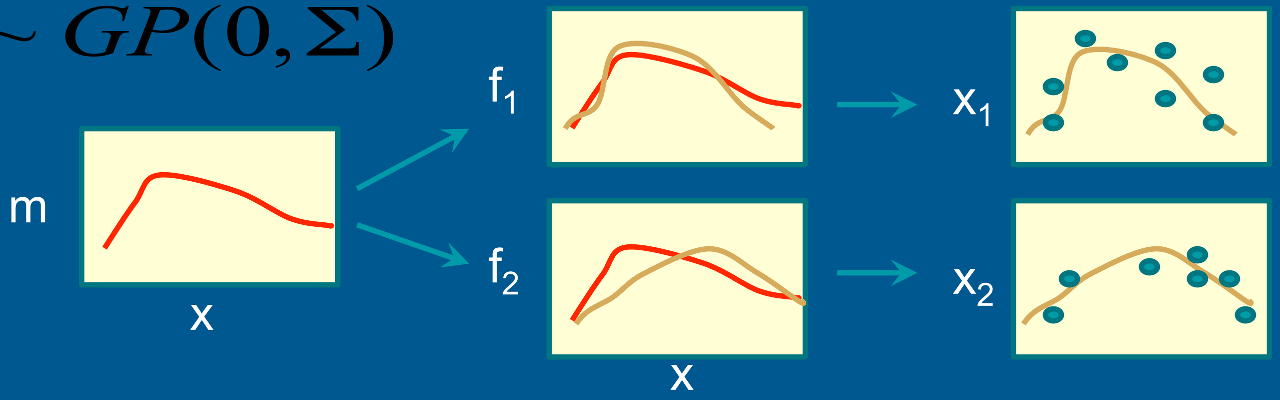
Two Locations
Competition
Yield ratio
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
0.1
0.2
0.3
0.4
0.5
Relative removal for non-target location (q)
Relative removal for non-target species (q)
GP
Ricker

Hierarchical modeling

Dynamics $x_{i,t} = f_i(x_{i,t-1}, x_{i,t-2}, \ldots, x_{i,t-d}) + \varepsilon_{i,t}$

GP prior $f_i \sim GP(m, C)$

Hyperprior $m \sim GP(0, \Sigma)$

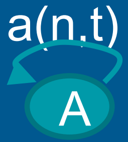


If we set $W = \Sigma + C, \quad \Sigma(x, x') = \rho W(x, x')$

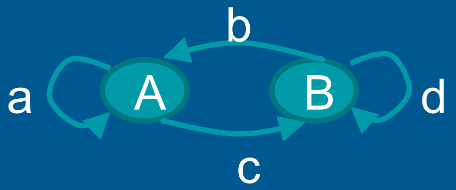
then $\rho = Corr[f_i(x), f_j(x)]$

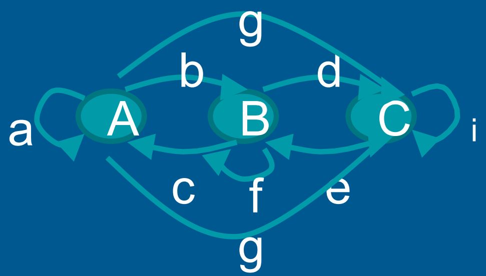
Simulation models

Density dependent maturation
Two locations with migration (2x)
Competition
Host-Parasitoid
Delayed density dependence (2x)
Maternal Effects
Time-varying population growth

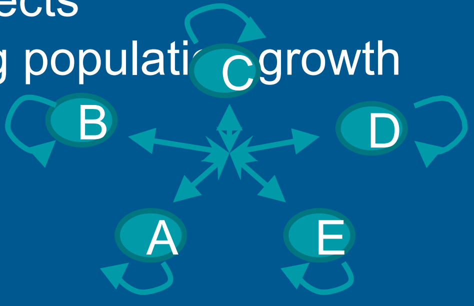


Density dependence



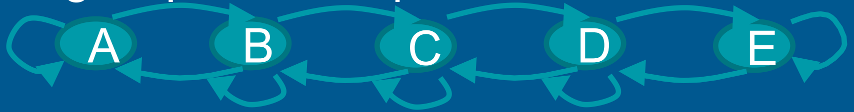


Contemporary evolution



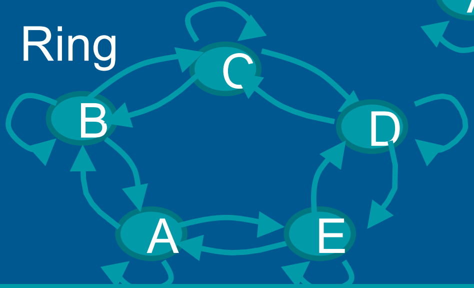
Pool

Single species in space

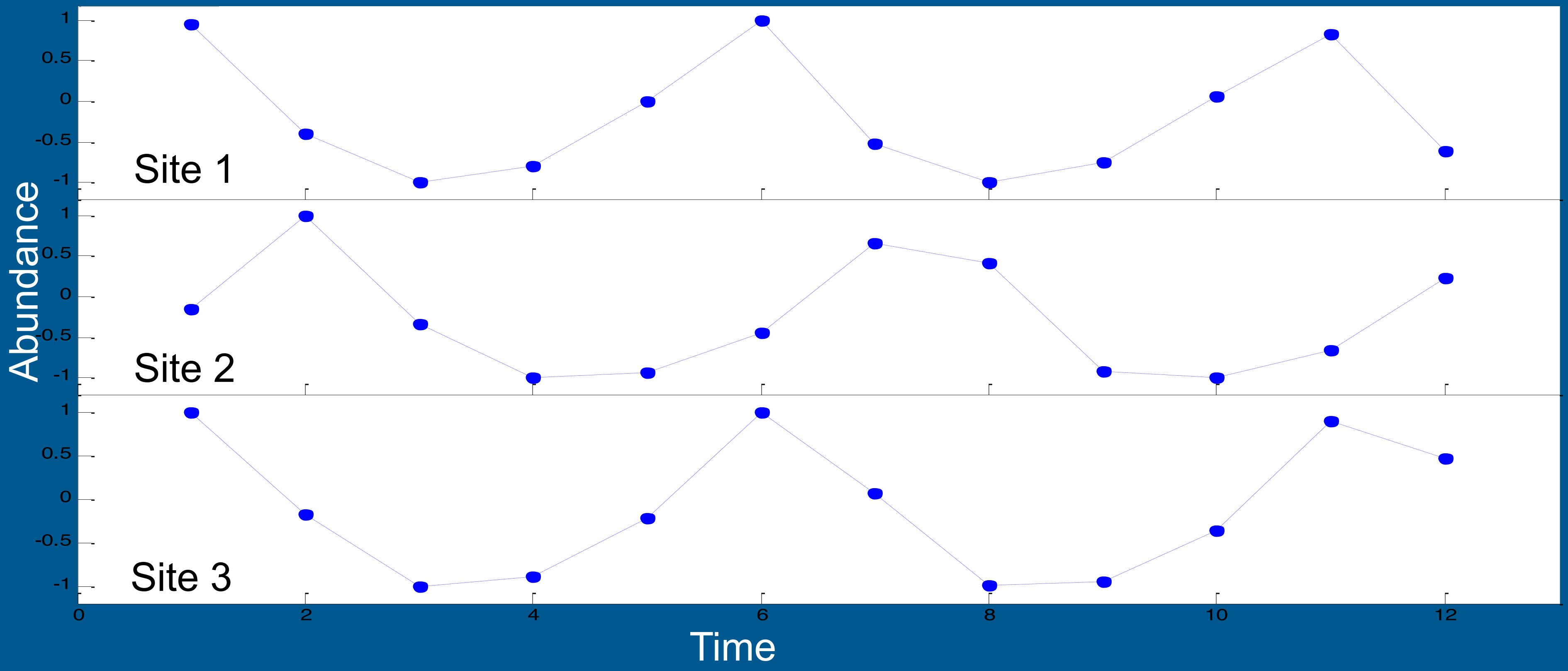


Line

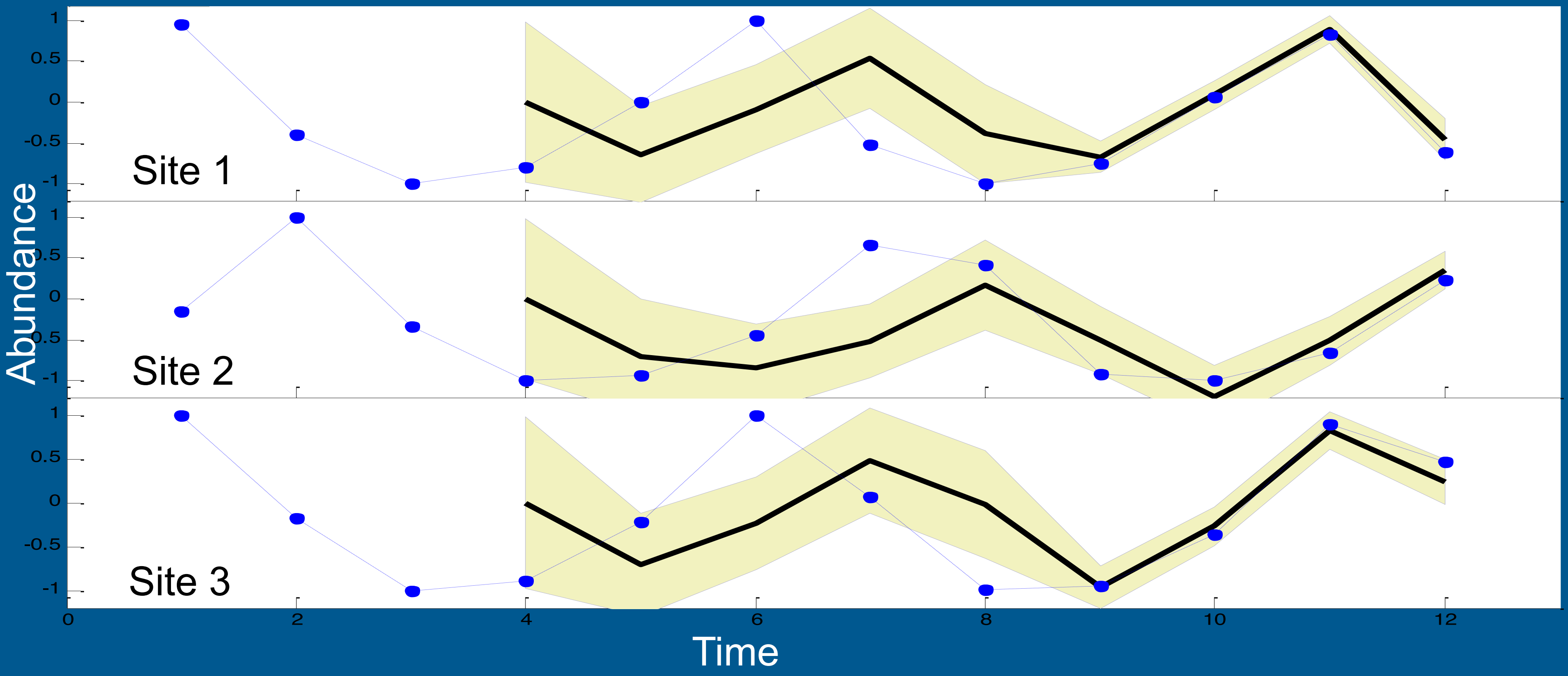
Ring



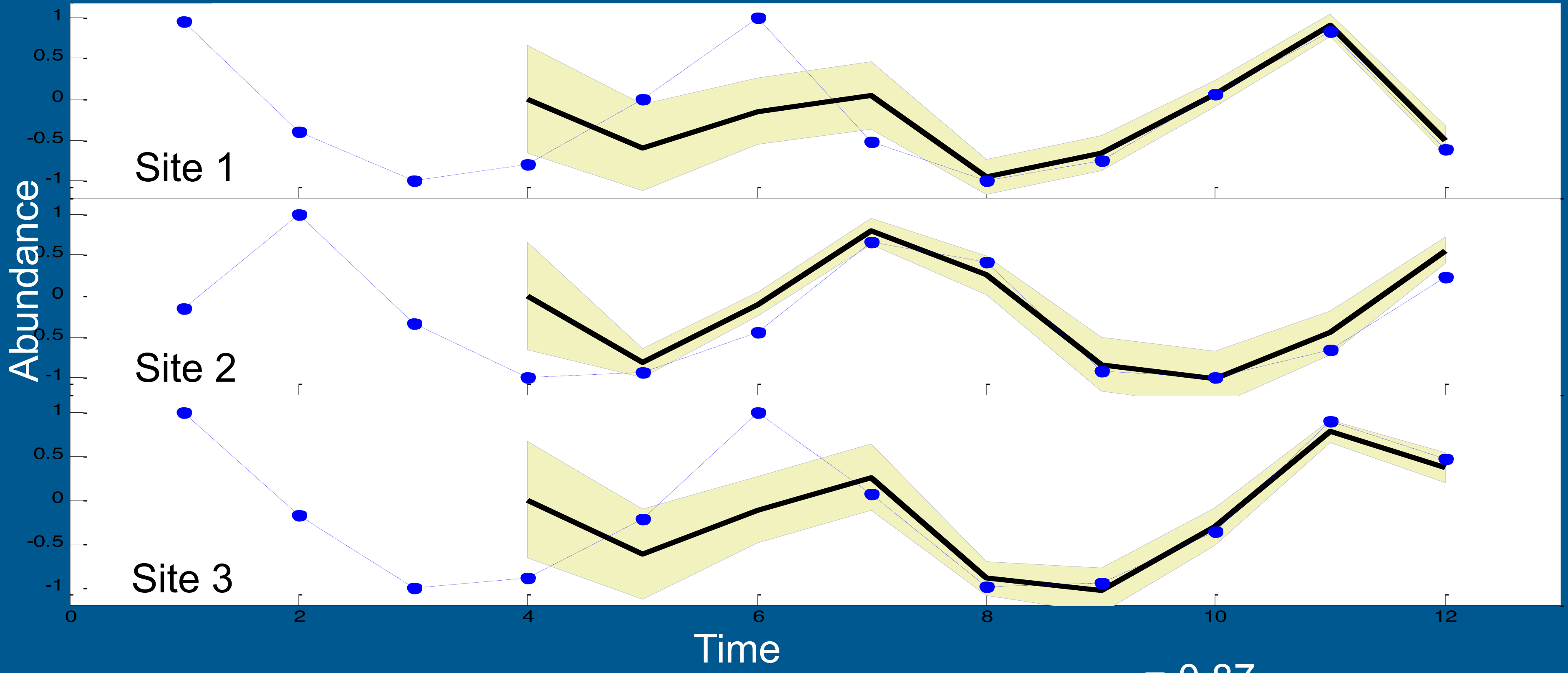
Multiple, short time series



Multiple, short time series: Modeled separately

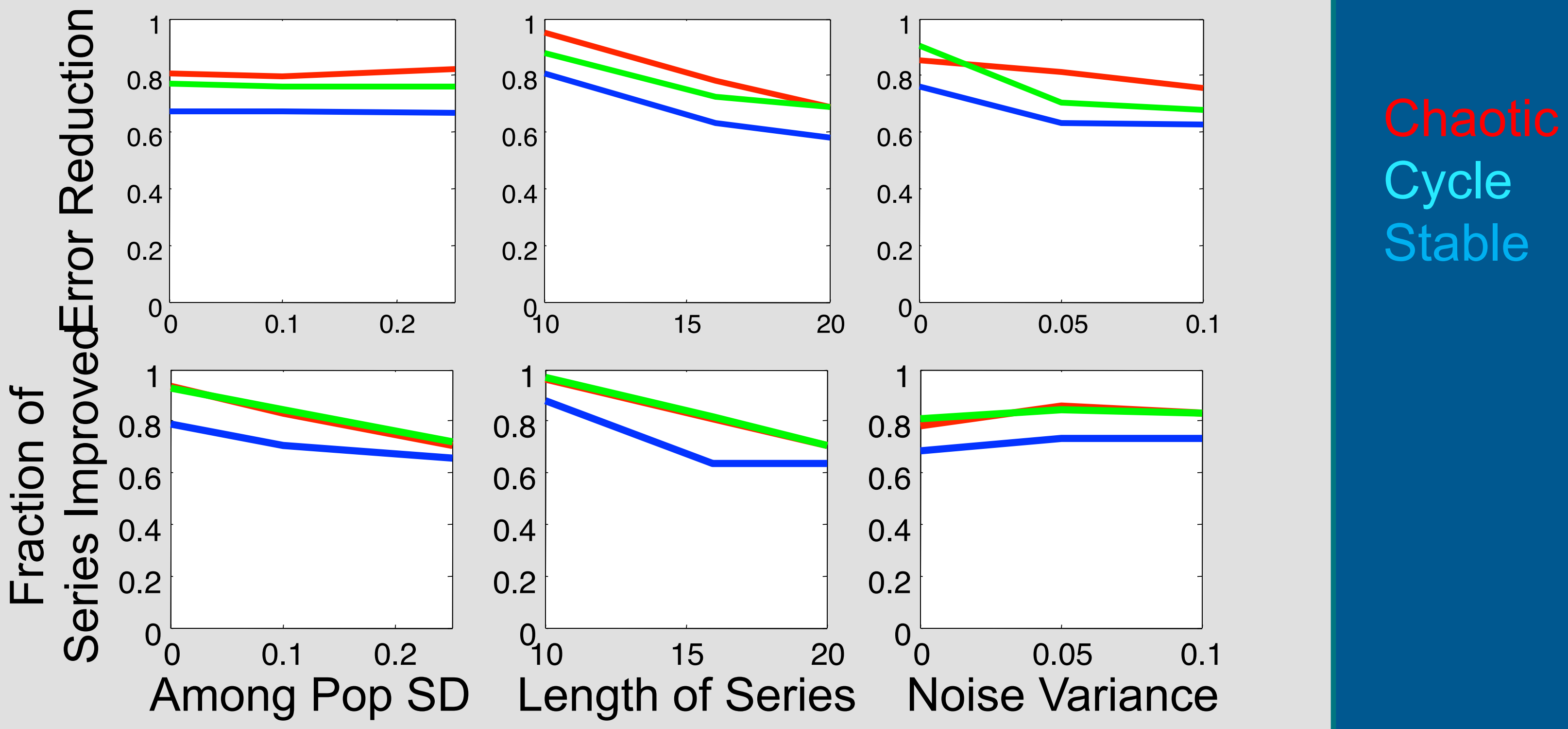


Multiple, short time series: Modeled hierarchically



$\rho = 0.87$

Results



Error Reduction
Fraction of
Series Improved
Among Pop SD
Length of Series
Noise Variance
Chaotic
Cycle
Stable

Nonstationary time series

Let *f* drift slowly through time to implicitly account for changing environments

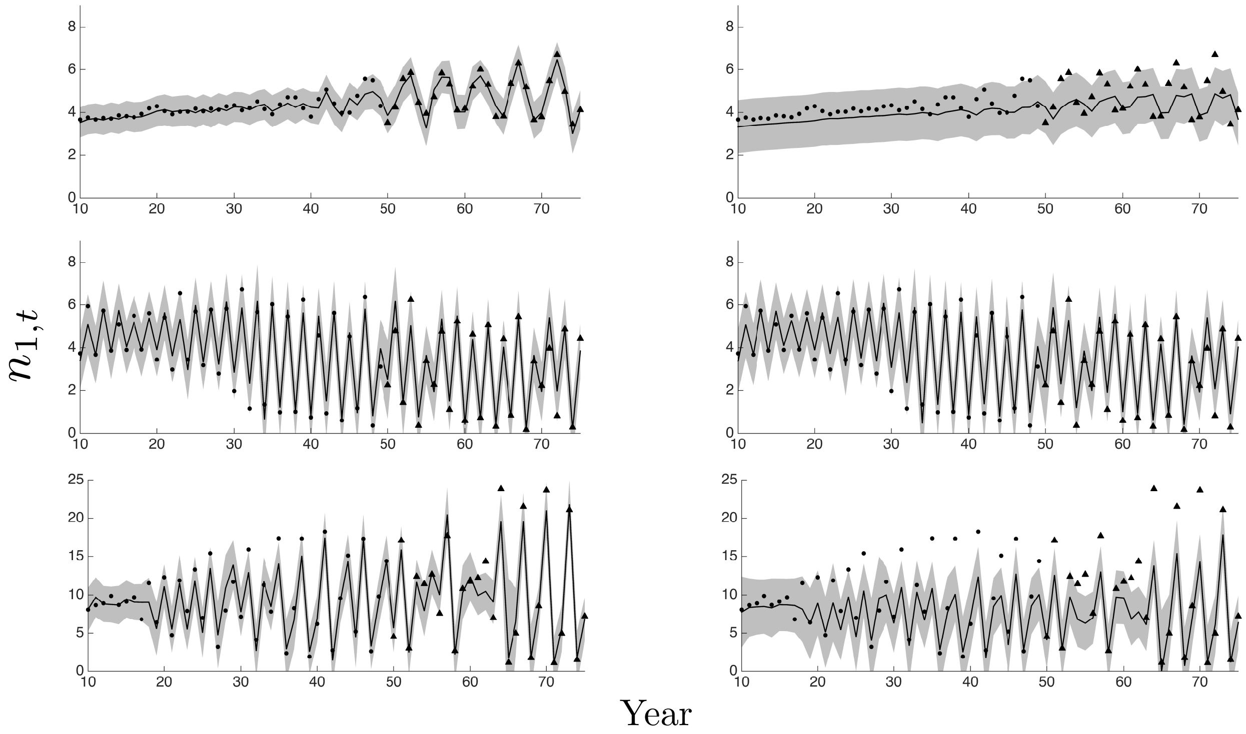
$$x_t = f_t(x_{t-1}, x_{t-2}, \ldots, x_{t-d}) + \varepsilon_t$$

$$f_t = f_{t-1} + \eta_t$$

$$f_0 \sim GP(0, C)$$

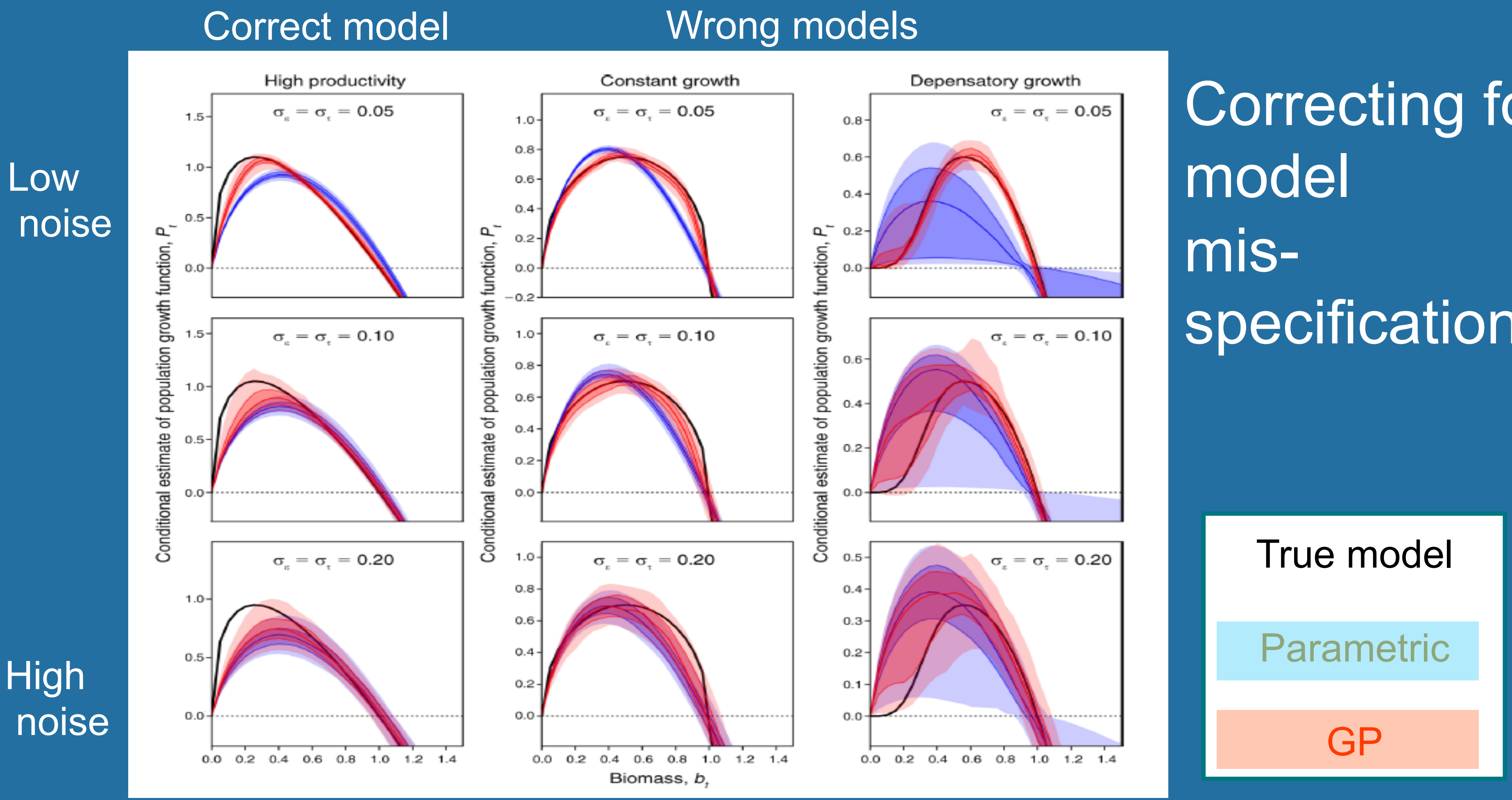
$$\eta_t \sim GP(0, W_t)$$

Allow *f* to change each step in an arbitrary way



Nonstationary embedding reduces forecasting error 5-40%

Correcting for model mis-specification



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Multi-objective programming: yield